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The Predictive Validity of University Admission Examinations: Case Study of Nigerian Unified Tertiary Matriculation Examination

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Abstract: For a sensitive university admission aptitude screening device like the Nigeria's Joint Admission and Matriculation Board's Unified Tertiary Matriculation Examination [JAMB-UTME], it is imperative that the predictive validity be constantly ascertained. The core objective of this study, therefore, was to establish the predictive validity of the JAMB-UTME. The case study and ex-post facto designs were used. The populations of study were the Senior Secondary School Leavers admitted to Nigerian universities via the JAMB-UTME. 8,139 students' records from a private university in Nigeria constituted the sample. The predictive power of the JAMB-UTME in predicting students' performance in the university's semester examinations was tested with regression model. The results suggested that the JAMB-UTME had positive but low indices of predictive validity, which varies across the academic sessions and programmes of study. It was not significant for some programmes. It was recommended that JAMB should embark on a more pragmatic review of the content of the UTME to enhance its predictive validity.

Keywords: learning; psychological testing; predictive validity; university entrance examination

Introduction

Accurate measurement is integral to all scientific measurements. It is the cornerstone of all scientific studies and inventions. It is therefore imperative that all scientific measuring instruments, especially psychological instruments that are measuring nebulous constructs, be ascertained for reliability and validity. Validity, however, is more important than reliability. This is because a measuring instrument can be reliable without being valid but hardly could a measuring instrument be valid without being reliable. Validity encompasses both concepts. Furthermore, the purpose of measurement also determines the degree of expected validity index. As a rule, when dealing with life sensitive issues, it may be to raise the level of validity indices for such measuring instruments. The JAMB-UTME currently used for admission into tertiary institutions in Nigeria fall into this category (Popoola et al., 2018). A number of students have attempted suicide when they fail to meet the JAMB-UTME cut-off points.

Amongst the validities essential for standardizing tests of this nature are content, construct and criterion-related validities. Predictive and Concurrent validities are under Criterion-related validities. Predictive validity shares similarities with concurrent validity in that both are generally measured as correlations between a test and some criterion measure. In a study of concurrent validity, the test is administered at the same time as the criterion is collected. In a strict sense of predictive validity, the test scores are collected first; then at some later time the criterion measure is collected (Odukoya et al, 2018). However, for the purpose of this study, the focus is on the Predictive Validity of JAMB's Unified Tertiary Matriculation Examination [UTME].

Predictive validity is the extent to which performance on a test is related to later performance that the test was designed to predict. For example, the SAT test is taken by high school students to predict their future performance in college (namely, their college Grade Point Average [GPA] or Cumulative Grade Point Average [CGPA]). If students who scored high on the SAT tend to have high GPAs of CGPAs in college, then we can say that the SAT has good predictive validity. But if there is no significant relation between SAT scores and college GPA/CGPA, then we would say the SAT has low or poor predictive validity, because it did not predict well (Cohen,1988).

AERA/APA/NCME (1999) reiterated that "validity evidence comes in many forms, and a sound validity argument integrates various strands of evidence into a coherent account of the degree to which existing evidence and theory support the intended interpretation of test scores for specific uses" (p. 17).

Joint Admission and Matriculation Board

The legal instrument establishing the JAMB was promulgated by Act (No. 2 of 1978) of the Federal Military Government. By August 1988, the Federal Executive Council amended Decree No. 2 of 1978. The amendments have since been codified into Decree No. 33 of 1989. It was this decree that empowered the JAMB to conduct Matriculation Examination for admission into all Universities, Polytechnics and Colleges of Education in Nigeria.

In 1974, seven Federal Universities were established in the country. At that time, each university conducted its own concessional examination and admitted its students. This led to serious limitations and waste of resources. This became a source of concern for the government and the committee of Vice Chancellors. In 1976, when the federal military government established six new universities, the challenge was escalated. Consequently, the government set up a national committee on university entrance examination under the chairmanship of Mr. M. S. Angulu. The committee recommended the setting up of two (2) bodies, the Central Admissions Board and the Joint Matriculation Board. The Federal military government decided to set up the Joint Admissions and Matriculation Board. The legal instrument establishing the Board was promulgated by Act no. 2 of 1978.

By August 1988, the Federal Executive Council empowered JAMB to conduct matriculation examinations for entry into all polytechnics and colleges of education in the Nigeria. The functions of JAMB as stipulated under Section 5 of Decree 33 of 1989 are as follows: The general control of the matriculation examination for admissions into all Universities, Polytechnics and Colleges of Education (by whatever name called) in Nigeria; the placement of suitably qualified candidates into tertiary institutions; and the collation and dissemination of information on all matters relating to admissions into tertiary institutions. Recently, the JAMB-UTME was conducted as Computer Based Test (CBT). It has emerged as one of the innovative approaches to assessment by examination bodies in the West African sub-region.

1.2 Research Questions

1. What is the predictive validity of JAMB-UTME based on students' CGPA across the academic sessions, 2005-2014?
2. What is the predictive validity of JAMB-UTME based on students' CGPA in the respective departments?

Method

Research Design

The ex-post facto design was adopted for this study since the study drew heavily on existing data – i.e. students' JAMB-UTME score at the point of entry into the university and their performance scores during subsequent the semester examinations.

Population and Sample

The population for this study were the undergraduate students of a private university in Nigeria. In all, 8,139 undergraduate students' participated in this study. The sample distribution is summarized in Table 1:

Table 1: Distributions on Demographic Data								
Academic Session	Frequency	Percent	College	Freq	Percent	Dept	Frequency	Percent
2005\2006	672	8.3	CDS	4369	53.7	ACC	874	10.7
2006\2007	900	11.1	CST	3769	46.3	ARC	312	3.8
2007\2008	669	8.2	Total	8139	100	BFN	322	4
2008\2009	729	9				BIO	324	4
2009\2010	1011	12.4	**Gender**	**Frequency**	**Percent**	BLD	85	1
2010\2011	442	5.4	Male	3805	46.8	BUS	789	9.7
2011\2012	1005	12.3	Female	4333	53.2	CHE	178	2.2
2012\2013	1573	19.3	Total	8138	100	CHM	98	1.2
2013\2014	1136	14				CIS	896	11
Total	8138	100				CVE	130	1.6
						ECO	872	10.7
						EIE	1108	13.6
						ESM	140	1.7
						LNG	134	1.6
						MAC	423	5.2
						MAT	56	0.7
						MCE	139	1.7
						PET	153	1.9
						PHY	150	1.8
						PSI	588	7.2
						PSY	174	2.1
						SOC	193	2.4
						Total	8139	100

Out of the total sample of 8,139, 53.2% were female while 46.8% were male. The programme with the highest sample size in this study was Electrical and Information Engineering [EIE] with 13.6%, followed by Accounting [10.7%] and Economics [10.7%]. The session with the largest sample size was 2012/13 with 19.3%.

Instrument

The instruments used to derive the data for this study were: the JAMB-UTMEs from 2002 to 2010 and the Semester examinations conducted by Covenant University [CU] from 2002 to 2014. The JAMB-UTMEs were wholly multiple choice objective tests. The CU semester examinations were mostly combinations of multiple choice questions and essay questions. The content validity of the CU examination questions, especially for final year students were determined by the judgment of external examiners. It is assumed that the reliability and validity of the JAMB-UTME have been established, considering JAMB is a professional examination body. However, such data have never been made public. Cursory inspections of the JAMB-UTME items suggest that the tests included some advanced level questions. The JAMB-UTME is actually a speed aptitude test designed for screening and admitting students into tertiary institutions. The CU semester examinations were predominantly achievement tests.

Data Collection

The Covenant University's Undergraduate Students' JAMB-UTME and their corresponding CGPA score were collected from the university's Computer System and Information Service [CSIS] data base.

Data Analysis

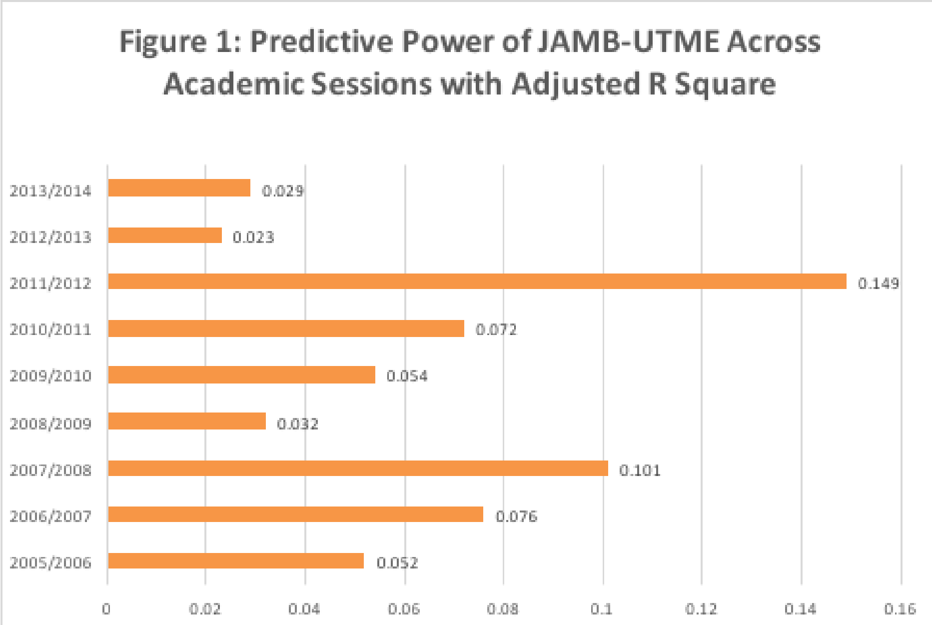
Since the focus of the study is to establish the predictive validity of JAMB-UTME, the statistics employed was simple linear Regression (Miles, & Shevlin, 2001). Data were re-grouped and analysed on the basis of academic session and students' department.

Results

What is the predictive validity of JAMB-UTME based on Students' CGPA across the academic sessions, from 2005 to 2014?

Table 2: Regression of JAMB-UTME over Students' CGPA by Academic Session [2005 to 2014]

ACAD SESSION	Model	Sum of Squares	df	Mean Square	F	R	R^2	Adjusted R^2		B	Beta	t	Sig.
2005/2006	Regression	14.081	1	14.081	38.14	0.232	0.054	0.052	Constant	2.333	0.23	15.194	0
	Residual	247.348	670	0.369					UTME	0.005		6.176	0
2006/2007	Regression	32.849	1	32.849	74.58	0.277	0.077	0.076	Constant	2.314	0.28	18.361	0
	Residual	395.533	898	0.44					UTME	0.006		8.636	0
2007/2008	Regression	34.516	1	34.516	76.17	0.32	0.102	0.101	Constant	2.036	0.32	12.74	0
	Residual	302.262	667	0.453					UTME	0.007		8.727	0
2008/2009	Regression	13.336	1	13.336	25.07	0.183	0.033	0.032	Constant	2.49	0.18	12.796	0
	Residual	386.683	727	0.532					UTME	0.005		5.007	0
2009/2010	Regression	24.693	1	24.693	58.27	0.234	0.055	0.054	Constant	2.447	0.23	17.161	0
	Residual	427.62	1009	0.424					UTME	0.005		7.633	0
2010/2011	Regression	18.681	1	18.681	35.45	0.273	0.075	0.072	Constant	1.873	0.27	7.466	0
	Residual	231.884	440	0.527					UTME	0.007		5.954	0
2011/2012	Regression	61.676	1	61.676	177.3	0.388	0.15	0.149	Constant	0.928	0.39	4.837	0
	Residual	348.861	1003	0.348					UTME	0.011		13.316	0
2012/2013	Regression	16.984	1	16.984	38.19	.154a	0.024	0.023	Constant	2.364	0.15	13.043	0
	Residual	698.596	1571	0.445					UTME	0.005		6.18	0
2013/2014	Regression	14.515	1	14.515	34.6	.172a	0.03	0.029	Constant	2.297	0.17	10.468	0
	Residual	475.755	1134	0.42					UTME	0.006		5.882	0



The highest index of JAMB-UTME's predictive validity with CU students' CGPA was featured in the 2011/12 session [R2 = 0.149 or 14.9% prediction] while the lowest was in 2012/13 session [R2 = 0.023 or 2.3% prediction]. Though all the results furnished significant regression models, the percentages of prediction were generally low in all the sessions

What is the predictive validity of JAMB-UTME based on Students' CGPA in the respective departments?

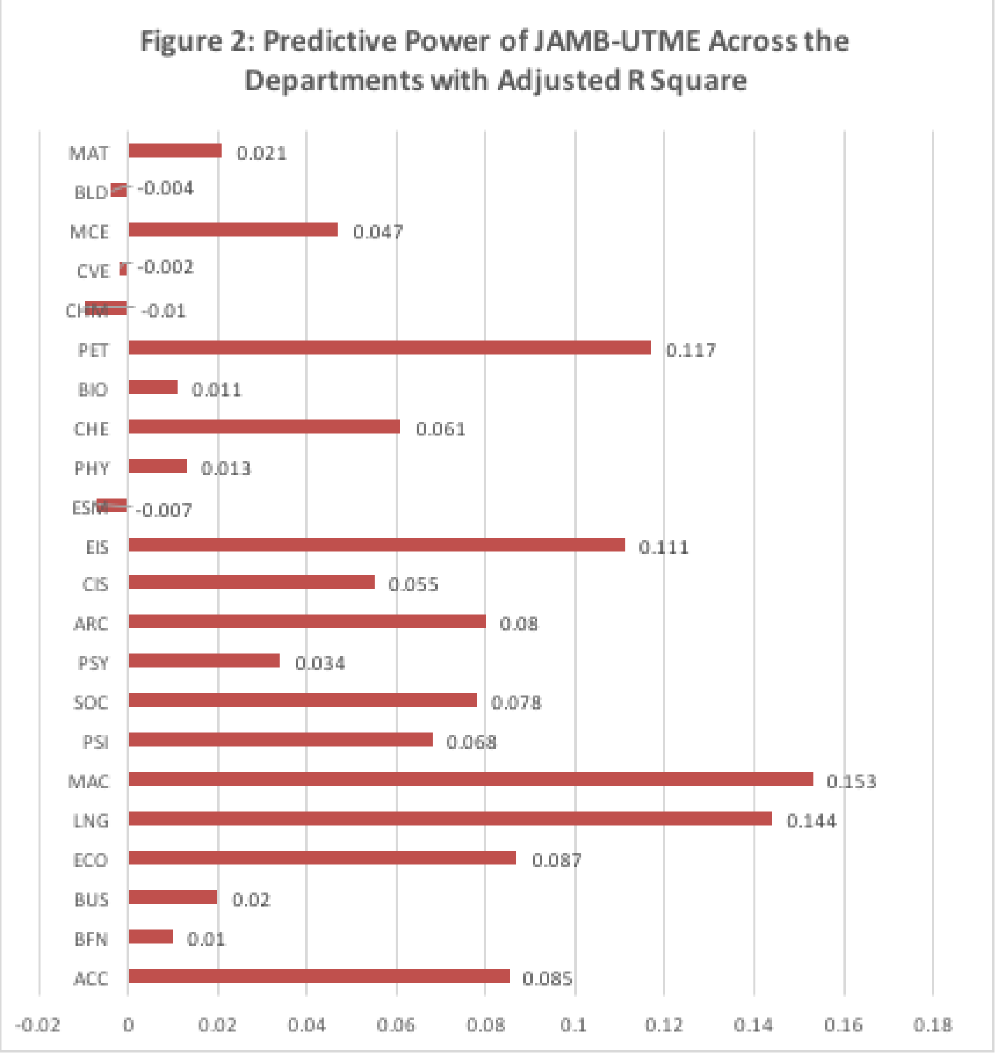
Table 3: Regression of JAMB-UTME over Students' CGPA by Department [2005 to 2014]

DEPT	Model	Sum of Squares	df	Mean Square	F	R	R^2	Adjusted R^2		B	Beta	t	Sig.
ACC	Regression	39.33	1	39.33	81.767	0.293	0.086	0.085	Constant	2.143		13.377	0
	Residual	419.439	872	0.481					UTME	0.007	0.293	9.042	0
BFN	Regression	2.174	1	2.174	4.329	.116a	0.013	0.01	Constant	2.686		10.384	0
	Residual	160.676	320	0.502					UTME	0.003	0.116	2.081	0.038
BUS	Regression	7.451	1	7.451	16.932	.145a	0.021	0.02	Constant	2.83		18.612	0
	Residual	346.339	787	0.44					UTME	0.003	0.145	4.115	0
ECO	Regression	37.913	1	37.913	83.673	.296a	0.088	0.087	Constant	2.07		12.751	0
	Residual	394.204	870	0.453					UTME	0.007	0.296	9.147	0
LNG	Regression	6.99	1	6.99	23.352	.388a	0.15	0.144	Constant	1.196		2.788	0.006
	Residual	39.514	132	0.299					UTME	0.01	0.388	4.832	0
MAC	Regression	26.892	1	26.892	76.957	.393a	0.155	0.153	Constant	1.662		8.728	0
	Residual	147.115	421	0.349					UTME	0.008	0.393	8.773	0
PSI	Regression	15.255	1	15.255	43.605	.263a	0.069	0.068	Constant	2.275		13.971	0
	Residual	205.012	586	0.35					UTME	0.005	0.263	6.603	0
SOC	Regression	7.37	1	7.37	17.176	.287a	0.083	0.078	Constant	2.161		6.729	0
	Residual	81.959	191	0.429					UTME	0.006	0.287	4.144	0
PSY	Regression	2.809	1	2.809	7.102	.199a	0.04	0.034	Constant	2.668		8.728	0
	Residual	68.03	172	0.396					UTME	0.004	0.199	2.665	0.008
ARC	Regression	9.368	1	9.368	27.925	.287a	0.083	0.08	Constant	2.307		10.61	0
	Residual	103.992	310	0.335					UTME	0.005	0.287	5.284	0
CIS	Regression	25.657	1	25.657	53.563	.238a	0.057	0.055	Constant	2.258		14.848	0
	Residual	428.231	894	0.479					UTME	0.005	0.238	7.319	0
EIS	Regression	57.427	1	57.427	139.25	.334a	0.112	0.111	Constant	1.984		14.903	0
	Residual	456.117	1106	0.412					UTME	0.007	0.334	11.8	0
ESM	Regression	0.029	1	0.029	0.079	.024a	0.001	-0.007	Constant	3.096		8.54	0
	Residual	51.069	138	0.37					UTME	0	0.024	0.282	0.779
PHY	Regression	1.183	1	1.183	2.893	.138a	0.019	0.013	Constant	2.45		4.17	0
	Residual	60.549	148	0.409					UTME	0.005	0.138	1.701	0.091
CHE	Regression	4.957	1	4.957	12.415	.257a	0.066	0.061	Constant	2.151		5.035	0
	Residual	70.278	176	0.399					UTME	0.007	0.257	3.523	0.001
BIO	Regression	2.32	1	2.32	4.73	.120a	0.014	0.011	Constant	2.727		7.559	0
	Residual	157.937	322	0.49					UTME	0.004	0.12	2.175	0.03
PET	Regression	6.441	1	6.441	21.046	.350a	0.122	0.117	Constant	1.789		4.481	0
	Residual	46.216	151	0.306					UTME	0.008	0.35	4.588	0
CHM	Regression	0	1	0	0	.002a	0	-0.01	Constant	3.514		6.332	0
	Residual	32.295	96	0.336					UTME	5.00E-05	0.002	0.02	0.984
CVE	Regression	0.353	1	0.353	0.78	.078a	0.006	-0.002	Constant	3.077		5.929	0
	Residual	57.893	128	0.452					UTME	0.002	0.078	0.883	0.379
MCE	Regression	3.216	1	3.216	7.813	.232a	0.054	0.047	Constant	2.341		5.252	0
	Residual	56.385	137	0.412					UTME	0.006	0.232	2.795	0.006
BLD	Regression	0.308	1	0.308	0.707	.092a	0.008	-0.004	Constant	2.744		4.141	0
	Residual	36.115	83	0.435					UTME	0.003	0.092	0.841	0.403
MAT	Regression	1.017	1	1.017	2.187	.197a	0.039	0.021	Constant	2.194		2.605	0.012
	Residual	25.101	54	0.465					UTME	0.006	0.197	1.479	0.145

***Keys**: ACC – Accounting; BFN – Banking & Finance; BUS-Business Managt; ECO-Economy; LNG-Language; MAC-Mass Communication; PSI; SOC-Sociology; PSY-Psychology; ARC-Architecture; CIS-Computer & Info Science; EIE [EIS]-Electrical & Info Engr; ESM-Estate Mangt; PHY-Physics; CHE-Chemical Engr; BIO-Biology; PET-Petroleum Engr; CHM; CVE-Civil Engr; MCE – Mechanical Engr; BLD – Building Tech; MAT - Mathematics*

The highest index of JAMB-UTME's predictive validity with CU students' CGPA across the departments was observed in the Mass Communication department [F (1, 421) = 76.96; p = 0.00; R^2 = 0.153 or 15.3% prediction] followed by the department of Languages [R^2 = 0.144 or 14.4% prediction] while the lowest was in department of Chemistry [F (1, 96) =

0; p = 0.98; R^2 = -0.01 or -1% prediction]. Though virtually all the results furnished significant regression models, the percentages of prediction were generally low for all the departments. It is important to note that the regression models obtained with JAMB-UTME and students' CGPA were not significant for departments of Chemistry [CHM], Civil Engineering [CVE], Estate Management [ESM] and Building Technology [BLD]



It is pertinent to note that the indices of predictive validity were not significant for the departments of Estate Management [F (1, 138) = 0.079; p = 0.779; R2 = -0.007 or -0.7% prediction], Chemistry [F (1, 96) = 0; p = 0.98; R2 = -0.01 or -1% prediction], Civil Engineering [F (1, 128) = 0.78; p = 0.379; R2 = -0.002 or -0.2% prediction] and Building Technology [F (1, 83) = 0.707; p = 0.403; R2 = -0.004 or -0.4%

prediction]. The adjusted R square value used here depicts the proportion or percentage of variance in the dependent variable [CU Students CGPA] that is explained by the independent or predictor variable [JAMB-UTME].

Discussion, Recommendations and Conclusion

The core finding from this study that the JAMB-UTME offered low indices of predictive validity from 2004 to 2014 and in virtually all the departments sampled [the highest adjusted R being 0.153] tend to find support from the finding made on the Iranian National University Entrance Examination into Medical school [popularly called Konkoor] when predicted against high school grade point averages. The Konkoor was a relatively poor predictor of medical students' academic performance. It was further reported that the predictive validity of the Konkoor tend to decline as the years spent in medical school increases (Farrokhi-Khajeh-Pasha et al., 2012 and Marques & Miranda, 1996). Khan, Mukhtar and Tabasum (2014) however, found that the estimated regression coefficient for Higher Secondary School Certificate scores was negative, while it was positive for entrance test, thus suggesting that the entrance test was a good positive predictor of performance in tertiary institution. Apparently, there are special skills to developing aptitude tests for admission purposes that would enhance their predictive power. This point, coupled with the fact there were no significant indices of predictive validity in four departments further point to the need for review of the Nigeria's Unified Tertiary Matriculation Examination [UTME].

Considering the sensitivity of the admission decision made on the basis of JAMB-UTME results over the years, the findings from this study call for urgent attention. JAMB is expected to develop aptitude tests that will offer higher predictive validity indices. This way, the JAMB-UTME would serve as a reliable and valid tool for screening and admitting students into different programmes of study in tertiary institutions. As Daramola et al (2017) rightly observed, in the short term, this is likely to minimize the frustrations experienced by students that are wrongly placed; and in the long run, the exercise is likely to culminate in enhanced national development as 'more round pegs are correctly placed in fitting round holes'.

Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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